# Simulating Complex Non-linear Dynamic Systems in Marketing

**Peter November and David Johnstone**
Victoria University of Wellington
PO Box 600 Wellington
New Zealand

Tel: 4 496 5431
peter.november@vuw.ac.nz and david.johnstone@vuw.ac.nz

Abstract

*An unusual feature of our approach to simulating complexity in marketing is that customers are represented as individuals, a thousand in the current simulation, rather than as an aggregate category or even segments. Because of this, we do not need to add random variables to account for behavioral variety within the customer domain during a simulation run. Each customer has an individual set of characteristics, termed their 'genetic code', corresponding to concepts from current buyer behaviour theory such as leader/laggardness, influence of advertising, reference group influence, and price/quality perception. Each simulated customer has decision-making processes that are affected by their genetic code, their memory, and the competitive marketing/supply situation.*

*Each supplier (competitor/brand) has a production capacity, which can be increased or decreased according to company policy and within any 'rules' that we choose to impose as programmers. Suppliers have decision-making processes that determine price, advertising, quality and stock levels. These are directed by strategies through which each company tries to achieve its long-term objectives. Different strategies and objectives can be set for each supplier.*

*Testing, development and experimentation are at an early stage, but to date the results, even with neutral supplier strategies, reflect non-linearity and complexity.*

## Introduction

Chaos theory, or to use the more modern term, complexity, is a topic that has received scant attention in the marketing literature. Hibbert and Wilkinson (1994) did a good job of explaining why turbulence should exist in marketing activity whereas Herbig (1991), Herbig and Goldern (1991), Mix (1993), and Smolowitz (1996) drew attention to the topic in a somewhat arms length way. For example the title of Mix's paper is "Is There Chaos in Marketing?" Probably the best managerial introduction to the topic is that given by Freedman (1992).

Many marketing academics seem to work under the delusion that they can build an understanding of marketing systems like a brick wall, one brick at a time, with different research groups working on different parts of the wall. This is the reductionist / incremental concept of knowledge: 1) Break a complex problem into parts. 2) Study each part. 3) Put all the studies together and you will understand the complex whole (Hunt 1983). As Freedman (1992) puts it:

> "Nineteenth-century physics, based on Newton's laws of motion, posited a neat correspondence between cause and effect. Scientists were confident that they could reduce even the most complex behaviors to the interactions of a few simple laws and then calculate the exact behavior of any physical system far into the future. . . . . But during the past few decades, more and more scientists have concluded that this and many other of science's traditional assumptions about the way nature operates are fundamentally wrong."

The marketing science approach, a requirement for all top marketing journals, is based on the Newtonian view and approach to science. Members of the marketing academic community who encourage colleagues to conduct traditional science-like studies based on reductionism are old fashioned in their understanding of science. A new approach to science is emerging. Again in the words of Freedman:

> "The way scientists identify the predictable patterns in a system has been turned on its head. Instead of trying to break down a system into its component parts and analyse the behaviors of those parts independently - the reductionist tradition - many scientists have had to learn a holistic approach. They focus increasingly on the dynamics of the overall system. Rather than attempting to explain how order is designed into the parts of a system, they now emphasize how order emerges from the interaction of those parts as a whole."

Levy (1994) gives an example of this holistic approach. He built a simulation of an international distribution system (not just part of a system). He shows that systems of this type can behave chaotically.

For readers unfamiliar with chaos theory, the term ‘chaos’ does not mean ‘out of control’ or ‘random’. It means ‘turbulent’ or ‘chaotic looking’. In fact there is an underlying pattern in this kind of behaviour whereas there is no such pattern in ‘real’ chaos.

To summarise, the literature suggests that marketing systems should exhibit chaotic behaviour but very little work, empirical, theoretical or simulated has shown that it does exist.

In this paper we show that if the conventional wisdom on buyer behaviour is correct, then turbulence is indeed present in marketing. Furthermore it is not just present, but is quite persistent. We built a simulation model of a marketing system by using conventional ideas from the standard marketing literature. Our intention was to investigate this model to see if there were particular conditions that resulted in turbulence. We were somewhat taken aback to discover that our simulation exhibited turbulence straight away. Indeed at the start we were hard pressed to find any condition that gave anything remotely like tranquility.

Our experimental work is only at the start and we have begun to find that some parameters do have critical values that result, not so much in stability, but in patterns within the turbulence.

**The Model**

Our objective was to build a model based on well-known concepts from what might be termed 'standard' buyer behaviour theory (see for example Engel, Blackwell, and Miniard 1995 or any other text on consumer buyer behaviour). We linked this to a supply side model in order to create a conventional supply/demand system that we could run over time. A flow diagram of the model, which is called MIST (Marketing In Systemic Turbulence) is given in figure 1.

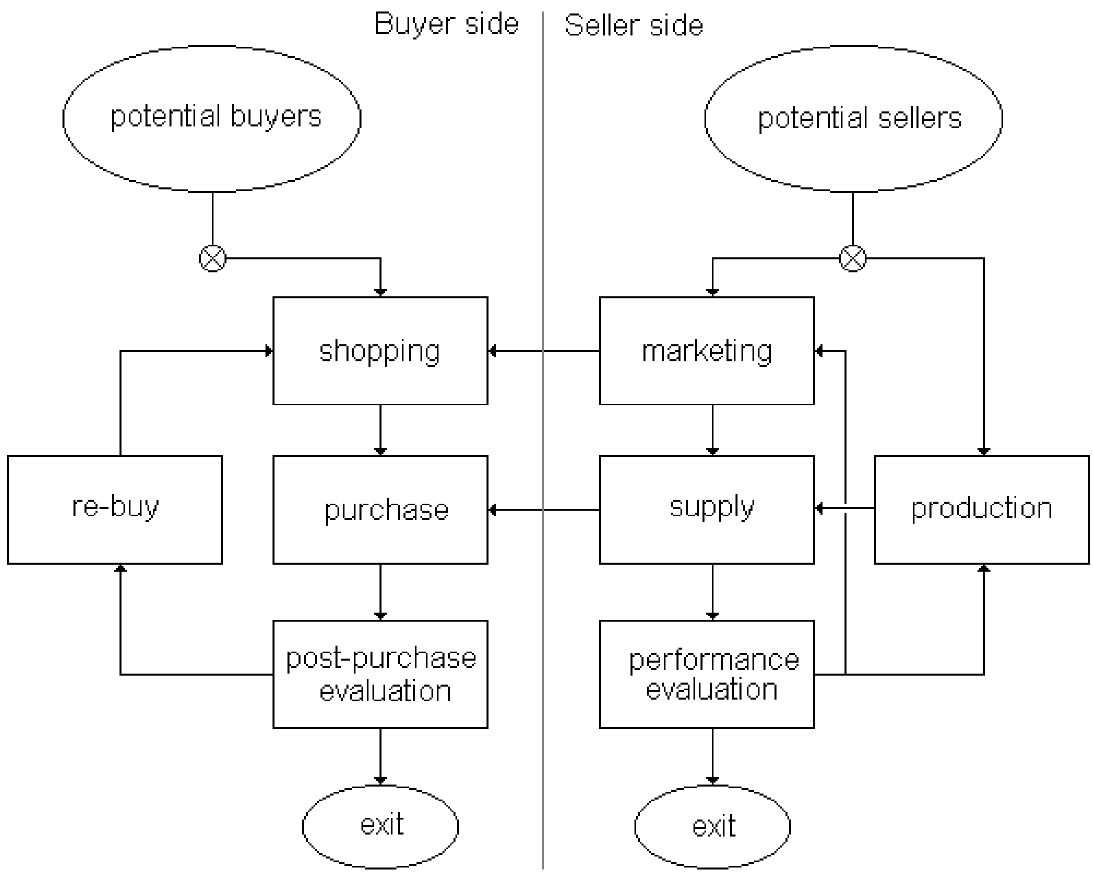


Figure 1: The MIST model.

We will explain how the model works in outline, referring to each of the parts in figure 1, starting with the buyer side.

'Potential buyers' is a set of explicit buyers that are defined individually before the model is run. In our work to date we have used one thousand buyers, though we have done a few experiments with two thousand buyers and with much smaller numbers. Each buyer in the set has individual characteristics, termed their *buyer genetics*. At present there are fifteen genetic variables for each buyer. They are:

> **G1: Maturity time.** This is the point in time when the buyer first joins the market as a potential buyer.

**G2: Consumption time.** This is the amount of time before the customer re-buys. When combined with G15, order size, this is the concept of heavy/light users.
**G3: End time.** The time when the buyer stops being interested in buying the product.
**G4: Influence of reference group.** A reference group is, for example, a set of friends, who influence your brand choice.
**G5: Size of reference group.**
**G6: Influence of experience.** This is relative importance to the buyer of his or her own experience of having tried and evaluated the brand in question.
**G7: Desired quality level.**
**G8: Influence of termed the marketing mix.** These are seller controlled marketing tools and normally comprise price, communication tools (such as advertising), product quality, and availability.
**G9: The influence of relative price.** This reflects the price of a brand compared with the prices of the other brands available.
**G10: The influence of relative advertising.** This reflects the amount of advertising expended on a brand compared with the expenditure on advertising on the other brands available.
**G11: The influence of relative availability.** This reflects availability of a brand compared with the availability of the other brands.
**G12: Single-mindedness v desperation.** Some buyers who only accept their first choice. They are termed ‘single-minded’. However there is a continuum down to a buyer who will even accept their last choice if nothing better is in stock. If the eventual choice is not in stock, then the buyer tries to buy again next time, rather than wait for their next re-buy time (G2).
**G13: Preferred advertising appeal.** Each buyer has an ordered set of advertising appeals.
**G14: Innovativeness.** Innovators are more likely to try new brands when they come out. This affects how they evaluate a new brand, relative to existing brands, that they know about. Innovators give a high initial score to new brands whereas laggards give them a low score.
**G15: Order size.**

At present these variables are allocated randomly but within finite limits to create a set of potential buyers before the simulation is run. This set of buyers can be saved and reused. Different sets of potential buyers can be built and tested.

In addition to these fifteen fixed characteristics (they do not change as the model runs), each buyer has a memory where they store their experiences. The memory variables are:

**M1: Old score.** This is the past overall rating of a brand and was used to make a purchase decision by comparison with the scores of the other brands that were on offer at that time. The initial value depends on the innovativeness gene (G14).
**M2: Old ref group score.** This is the buyer's rating of each brand based on his or her reference group influence.
**M3: Old experience score.** This is the buyer's rating of the brand on the basis of his or her experience with the brand.

**M4: Old mix score.** This is the buyer's rating of each brand based on his or her past experience of the brand's seller controlled variables.
**M5: Old reliability.** This is the buyer's rating of a brand based on his or her past experience of the brand's availability.

'Potential sellers' is a set of explicit sellers that are defined before the model is run. In our work to date we have used from two to nine sellers. Each seller in the set has to make seven decisions.

**D1: Start time.** This is the point in time when a seller offers its brand to customers.
**D2: Capacity.** This is the maximum quantity that a seller can make in any time period. It has an associated fixed cost.
**D3: Quality level.** This is taken as the variable cost expended when producing the product.
**D3: Price.** The price for one unit of the product.
**D4: Adspend.** The expenditure on communicating with potential customers in a time period.
**D5: Ad message.** The type of advertising message applied to the brand.
**D6: Minstock.** The stock control policy that, combined with the sales forecast, results in a particular stock level at the start of each time period.
**D7: End time.** The point in time when the seller decides to stop offering their brand to the market.

In addition to these decisions, each seller keeps business accounts that are updated at the end of each time cycle. Our simulation run lengths have typically been in the region of 600 cycles.

The buying process involves three stages: shopping, purchase, and post-purchase evaluation.

In the shopping phase, each buyer interested in buying at that point in time assesses the brands on offer in that period of time. They take into account their own prior experience of the brand (if any), the influence of their reference group, and the seller controlled marketing tools of price, advertising, and availability. From these considerations the buyer puts the brands on offer into a rational preference order. Note however that different buyers may well assess the brands differently because they are different genetically.

In the purchase phase the buyer tries to buy the required quantity (G15) of their most preferred brand. If the brand is not available the buyer's response depends on their single-mindedness (G12). They either try for their next best choice or they defer buying to the next time. They also remember that it was not available (M5).

Post-purchase evaluation leads to the formation of an experience memory (M3). It also leads to either a re-buy condition, meaning that they consume the brand at the normal consumption rate (G2) and re-buy after the appropriate time has elapsed, or to exit if their end time (G3) has been reached.

At present the selling process is much simpler than the buying process. All the decisions for each seller are fixed at the outset. All sellers remain in the market, irrespective of financial results.

Adjusting the genetic limits of the buyers can simulate many kinds of market dynamics. For example a one-time-buy fad-type market can be simulated by setting consumption time long (G2) and end time short (G3). A long-term, frequent purchase market can be simulated by setting consumption time (G2) fairly short and end time (G3) very long. Mid-range market dynamics can be simulated as well as different market types and competitor structures.

**Early results**

To date we have focused on brand share change over time in frequently purchased, long-term markets. Our very early runs of the model were with the normal mixed bag of buyers (1000) and with a mixed bag of sellers (9). That is with seller decisions such as price, advertising and availability all set differently. This gave satisfyingly chaotic results straight away. We then set the seller decisions to be all the same and expected very little chaos. We were quite wrong.

Because the underlying structure of the model uses a large number of buyers, each with a unique genetic structure, the simulation is 'naturally' turbulent. Because each buyer can be influenced by other buyers as well as influencing other buyers, the resulting network of interactions is dynamically complex. This complexity is an inherent part of MIST.

Figure 2 gives an example of output for market share with seven identical sellers. It is drawn to a large scale.

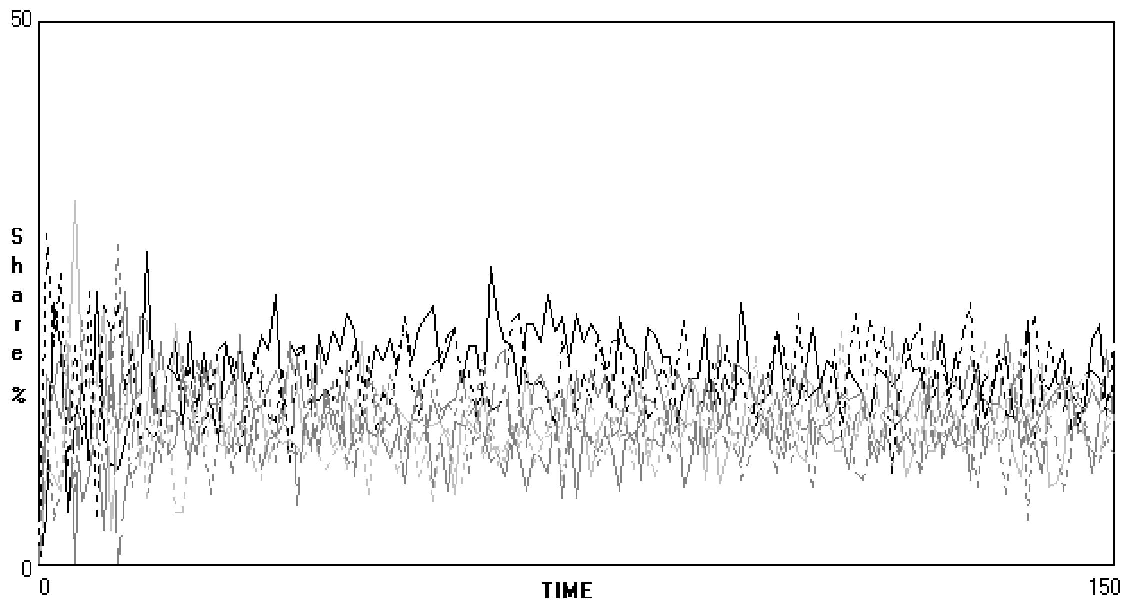


Figure 2: MIST Share % for 7 sellers and 1000 buyers.

Figure 3 gives the same results but with six sellers suppressed from the graphic so that you can follow an individual seller more easily.

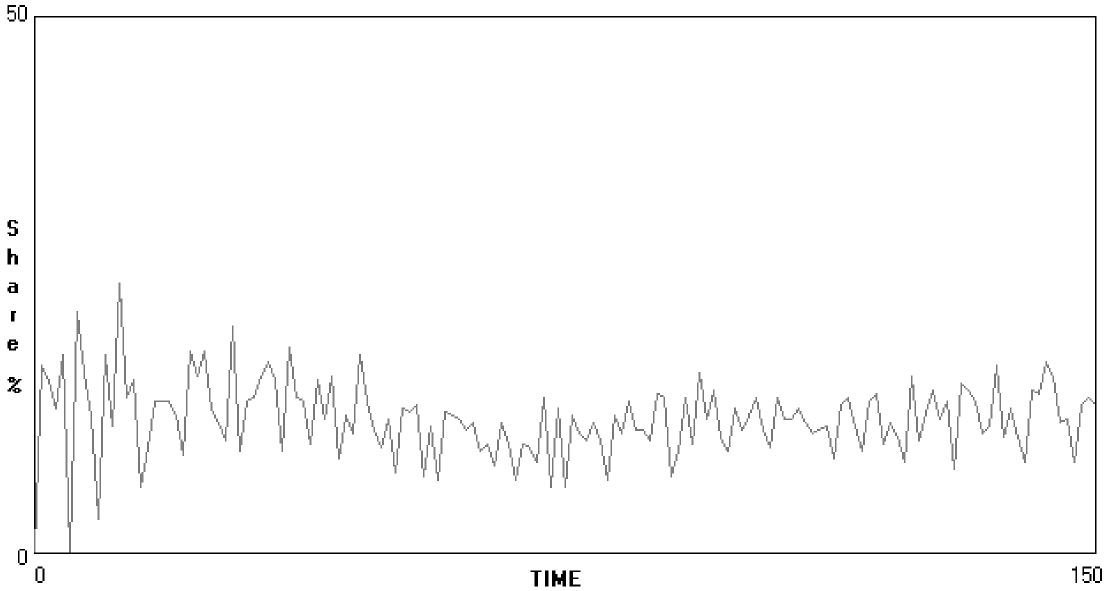


Figure 3: MIST Share % for 1/7 sellers and 1000 buyers.

On further experiment we noted that sometimes we got a persistent turbulent mixture, as in figure 4. This graph is drawn to a smaller scale than figures 2 and 3. It shows that the seven sellers, on average, had the expected brand share of about 14% but this varied over time between 4% and 25%.

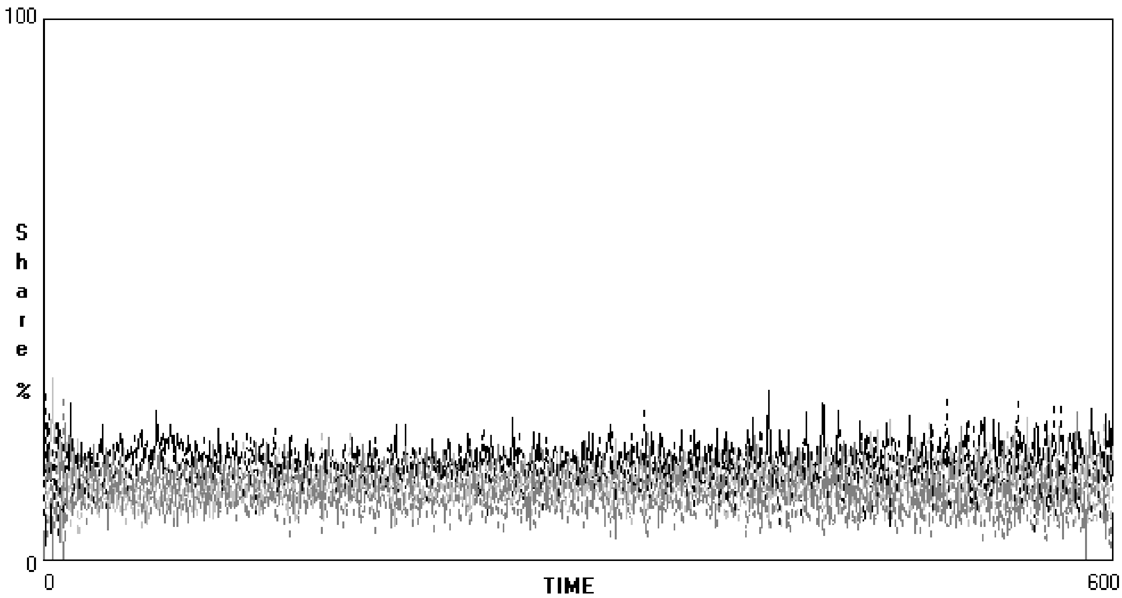


Figure 4: MIST Share % for 7 sellers, 1000 buyers, minstock 30.

At other times we got what we call *breakaway* as in figure 5. When breakaway occurs one of the sellers becomes dominant even though all sellers are set the same. We found that this breakaway condition was mainly determined by the setting of the parameter minstock, the minimum stock level carried by all sellers. Thus in figure 4 minstock is set at 30 whereas in figure 5 it is set at 20. In both cases all other parameters and the buyer set are identical at the start.

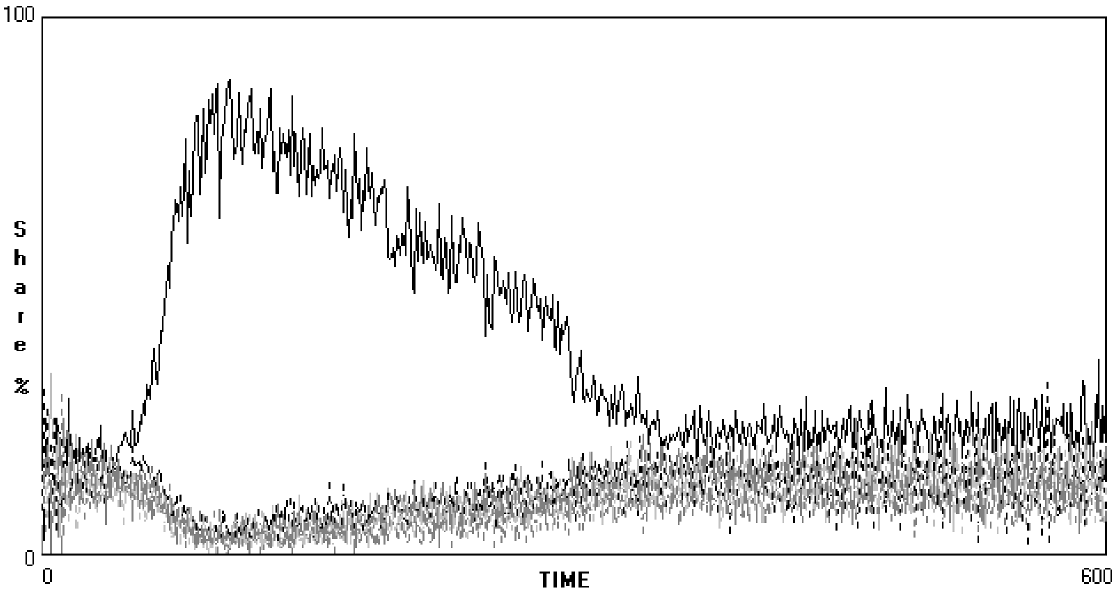

Figure 5: MIST Share % for 7 sellers, 1000 buyers, minstock 20.

Further tests showed that a critical value for minstock was 25 units. By ‘critical value’ we mean that the model behaves significantly differently each side of this setting.

We also found that the number of sellers affects breakaway. Figures 4 and 5 were obtained for 7 sellers. If we increase the number of sellers to 8 (all identical and the same as the earlier 7 sellers), use the same set of buyers, and rerun the tests, we find that the critical value of minstock has shifted to 23. Repeating the process at 9 sellers gives a critical value of 21 and reducing the number of sellers to 3 gives a critical value of about 53 (critical values are less clear at small seller numbers).

Further tests using different sets of buyers showed that while buyers have little effect on critical values, they did affect which seller broke from the group. For example in figure 6 breakaway is at a minstock of 20 but the seller is not the same as in figure 5.

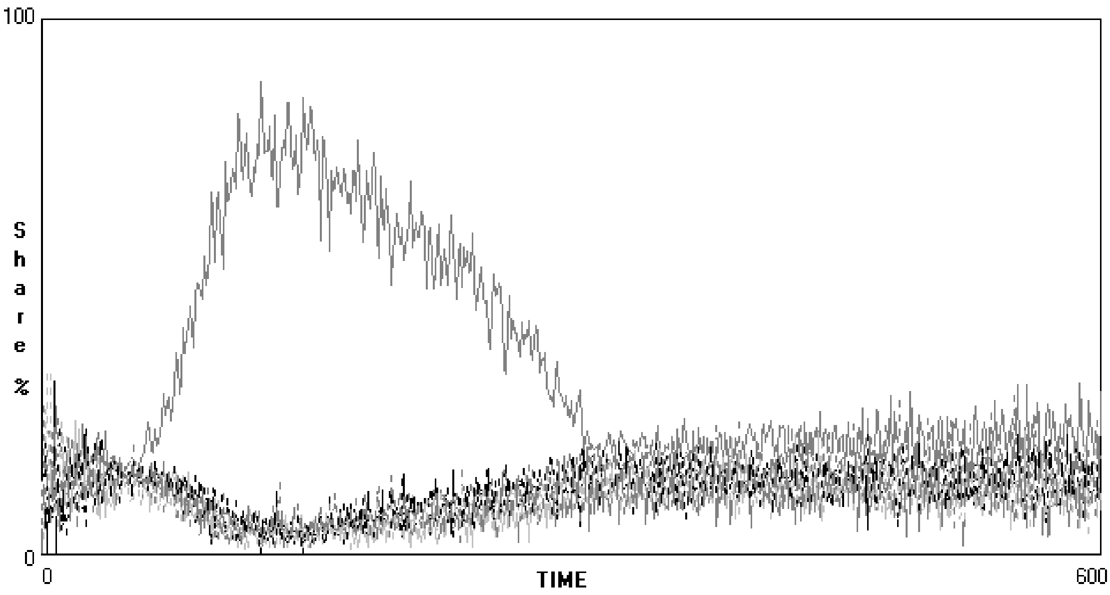

Figure 6: MIST Share % for 7 sellers, 1000 different buyers, minstock 20.

This variety in brand share pattern, depending as it does on a small number of parameters, is encouraging since a similar phenomenon has been found in other complex systems (May 1976, Feigenbaum 1980, Cvitanovic 1993).

**Further work**

We are still working on the simulation design, interface, and operating system while we test the simulation. This is normal for an exploratory simulation since we get design ideas as we think of new tests to run.

One significant area of future work is in the seller side of the model. At present this is crude. No seller decisions are made real-time whereas the buyer side comprises well-developed real-time decision process. For example, sellers have no way of opting out, irrespective of how unprofitable the business may be.

On the buyer side we plan to develop a genetic variable allocation system that can use explicit distributions rather than the current uniform random allocation.

Another area we plan to develop is the graphical output. At present this is only market share. Many other output variables are interesting, but particularly profit/loss.

Finally and perhaps of most importance, we hope to contribute to the greater understanding of marketing systems in a way that is useful and relevant to practitioners.

**Conclusions**

In the introduction we alluded to the fact that the literature on marketing seemed oddly devoid of material on chaos theory. Our work suggests that turbulence is quite normal in marketing if one models the conventional wisdom on buyer behaviour at the level of individual buyers and one allows for buyer variety. In addition, we hope this paper shows that the direct modeling of complex systems in marketing may provide useful insights for marketing practitioners.

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